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Simulation of spatially correlated wind power in small geographic areas—Sampling methods and evaluation

Guzmán Díaz *, Pedro G. Casielles, José Coto

Dep. of Electrical Engineering, University of Oviedo, Campus de Viesques, s/n 33204, Spain

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ABSTRACT

In clusters of wind generators spread over small geographic areas, the spatial correlation of wind power production is strong. Simulation of joint power production in such cases—such as for instance for determining the available power in a microgrid—is flawed if the correlation is not properly defined.

Several methods have been proposed in the literature for producing scenarios of correlated samples; mostly focused on wind speed. In this paper we analyze three popular choices: classical Monte Carlo (with correlation induced by Cholesky factorization), Latin Hypercube Sampling (with correlation induced by rank sorting), and the recent copula theory. We put together a variety of statistical tools to transform an uncorrelated multivariate sample into a correlated one; and supplement other works by introducing a detailed definition of the wind power distribution and by expanding the Archimedean copula analysis to dimensions beyond the bivariate case analyzed in some related works.

We analyze a year of wind production of 210 wind site from NREL data base. We cluster them to give a view of prospective microgrids, and employ several statistical techniques to measure the adequacy of the simulated samples to the original measured data.

Our results show that, for generation in small geographic areas, the higher the number of generators, the better the wind power dependence structure is described by LHS. On the contrary, copulas—Gumbel or Gaussian for two- and three-dimensional problems, and Gaussian for higher dimensions—are better suited for representing correlated wind speed. The results are different when the generators are spread over large geographic areas.

Compared with LHS endowed with rank sorting for inducing correlation, copula theory is in some sense cumbersome to apply for modeling and simulating wind power data. However, simulations can be performed in prospective microgrids in small geographical areas with larger accuracy by means of LHS if wind power is analyzed rather than wind speed. This advantage is lost for large distances or when small number of generators is considered.

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1. Introduction

The concept of microgrid has been evolving over the last decade to encompass a new paradigm of power system—that of a small in size cluster of distributed generation and loads, which can be managed to obtain economic and technical advantages. From the early discussions about modeling issues and grid connected versus islanded control [1–4] the research has focused in the last years on more realistic problems in which the microgrids might play a role in supporting the main grid [5], would harness renewable energy resources, optimize their operational costs [6,7], or take part in electricity markets [8–10]; with demonstration projects such as in [10,9].

Our paper is focused on wind power in microgrids, and more particularly on the simulation of wind power to obtain scenarios of interest for stochastic programming approaches. Wind power generation introduces an uncertainty in the model that prevents from analyzing the aforementioned problems in a deterministic way. See for instance [7], where Monte Carlo simulation of parametric (Weibull) distributions had to be employed to account for the uncertainty of wind energy in a unit commitment problem. Or the instance in [11], where Monte Carlo samples were also employed to define an interesting index, from balancing voltage security and loss reduction, which allowed determining the optimal reactive droop coefficients.

* Corresponding author. Tel.: +34 985182592.
E-mail addresses: guzman@uniovi.es (G. Díaz), pcasiell@uniovi.es (P.G. Casielles), jcoto@uniovi.es (J. Coto).

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Though in general stochastic programming is still being initially and progressively introduced into microgrid analyses, see for instance [11–14], in bulk power systems it has been thoroughly employed in the past; and the need for simulated wind scenario generation has been thus recognized. Moreover, spatial correlation has been recognized as a fundamental concept in determining accurate scenarios [15–22]. Mostly when as for instance is reported in [23–26] (and as we later justify) the correlation among close wind generators—those of a microgrid—is not negligibly but really strong. This is the subject matter of our paper.

The first of the techniques that we shall discuss is based on the notorious Monte Carlo simulation method. Some authors have proposed that uncorrelated Monte Carlo samples of wind speed can be transformed into correlated samples by means of a Cholesky factorization of the covariance matrix [15,19,20]. It is a relatively computationally inexpensive and simple method, which nevertheless has been already reported to have some problems with the production of unreal negative wind speeds. But more importantly, its major flaw may be in that the method is best suited for representing normal random variables, and thus its accuracy for modeling non-normal wind data may be thus compromised.

The second technique, Latin Hypercube Sampling (LHS), is considered in many related literature as an improvement over crude Monte Carlo. LHS is a technique that reduces the variance with respect to Monte Carlo and, maybe more important, is distribution free. In our case, the correlation must be again induced into the uncorrelated sample. We will follow the technique proposed by Iman and Conover in [27], which has been already employed to induce wind correlation samples in [28,29].

Lastly, we will address copulas. As we shall show, it is a sophisticated technique that has been employed in recent wind speed related papers [30,25,22,31,32]. The proposition of copula theory is that the dependence structure among wind powers can be split into independent univariate marginals and a joint distribution function with uniformly distributed marginals, namely the copula. This dissociation is really advantageous, because marginals and copula can be managed independently. This is possible, however, at the cost of greater complexity in some analyses. For instance, Gumbel copula has been rarely employed, and only recently it has been analyzed in some papers, with favorable assessment about their accuracy in representing the dependence structure of wind power [30,32]. Nonetheless, the works in [30,32] have only addressed *bivariate*copulas—i.e., the dependence structure between two sites. Herein, we will show a procedure to expand the analysis to larger dimensions, so that a microgrid composed of several wind generators can be analyzed.

Specifically the following are novelties addressed in this paper, which to our knowledge have not been yet covered in the literature:

1. We introduce wind power as the random variable of interest, proposing an explicit formulation of the probability integral transform. Most of the literature deals with wind speed rather than wind power. However, directly employing wind power is of interest for some problems, such as those in which convolution of random variables is required—for instance to aggregate all produced random power in a microgrid or wind farm [33]. But the use of wind power as a random variable is complicated by the existence of "jumps" in the distribution function because of the constant or null power produced by the turbine at some speed ranges. This entails that for instance the direct application of the probability integral transform makes a copula definition non-unique. We then propose a mixed discrete–continuous formulation, derived from Rüschendorf's work in [34], which permits a simple transformation of wind power into uniform variables.
2. Our analysis is cross-sectional—rather than based on time series—and multivariate. This means that we study spatial correlation, which has been the subject matter of some papers cited above. Again, this is necessary for analyzing clusters of wind generators spread over small geographic areas—such as wind farms and microgrids. In this respect recently some papers have introduced copula theory. The novelty in our paper is that we extend the analysis to *multivariate Gumbel* copulas. So far only *multivariate Gaussian* and *bivariate Gumbel* copulas had been employed; though it is remarkable that in [30,32] it was concluded that Gumbel copulas are best suited in many cases to represent the dependence structure of wind speed than Gaussian copulas. It thus seems interesting to know whether this is also true in scenarios involving more than two generators. Specifically, we have not found any published work related to energy analysis in which a non-iterative procedure for modeling multivariate Gumbel copula is detailed.
3. After addressing the modeling issues, we make a comparison of three methods for random simulation: LHS, Monte Carlo, and copulas. This is of concern for stochastic programing, where wind power scenarios must be obtained. Nonetheless, we have not either found in the literature any guidance about which of the three methods performs best. Monte Carlo is the most simple and copula the most demanding. So the question that we address is: Is the complex copula theory required to properly simulate wind power/speed scenarios?
4. We have not found in energy related literature ways of assessing the goodness of cross-sectional wind simulated data. We propose the use of two methods. One for bivariate data, based on two-sample tests, and other for multivariate data, based on DD-plots first introduced in [35].
5. Finally following point 3, we provide guidance on which of the methods is best suited for representing dependence structures in a wind scenario generation framework. Our results, based on real data, indicate that the answer depends on the distance among generator sites, the dimension of the problem (number of generators), and the random variable analyzed (wind power or wind speed). We conclude that though more complex, copula theory is not always the best choice—for instance, high dimensional problems analyzing wind power are better represented by the less complex LHS.

The paper is then structured as follows. Section 2 shows the techniques employed to generate simulated samples of spatially correlated wind powers. Section 3 describes the quality assessment techniques and evaluates the goodness of each approach. Last Section concludes.

2. Preliminaries and description of methods

2.1. Mixed formulation of the wind power distribution

A fundamental and common aspect of the methods analyzed herein is their use of uniform random variables for a number of sampling computations. This is a requirement in every method analyzed here. In our analysis of copulas, we will transform the wind power into uniform scale-less variables to fit copula families and simulate (uniformly distributed) samples. Thereafter, we shall return to the wind power true value. In LHS simulations, we shall depart from stratified uniform samples and transform the obtained quantiles into wind power. Similarly, we will obtain uniform samples to produce wind power by transformation, and thereafter introduce correlation.

If we let $F_{P_i}(P_i)$ be the cumulative distribution function (CDF) of wind power, a random variable, the probability integral transform

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